Improvement of aerodynamic properties of high-speed trains by shape optimization and flow control

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Abstract

Increase in speed of new high-speed trains has led to new requirements for improvement of their aerodynamic properties. Aerodynamic properties such as drag, crosswind stability, aeroacoustics noise and upraise of ballast due to flow have to be treated simultaneously in a multi-objective optimization procedure. This paper demonstrates an efficient optimization procedure that uses metamodels in form of polynomial response surfaces as a basis for search for optimal designs. Such simple models of objective functions make it possible to use genetic algorithms to explore design space. As a result of the suggested optimization procedure a set of so called Pareto-optimal solutions was obtained that helps exploration of extreme designs and finding tradeoffs between design objectives. Two examples are demonstrated for the purpose of the validation of the optimization procedure: optimization of a front of a train for the cross-wind stability and the optimization of passive flow devices (so called vortex generators) for drag reduction. Influence of turbulence models used in computer experiments on optimization procedure is explored. It was found that the choice of turbulence model influences the shape of the train with minimal lift force. Usage of Reynolds Stress (RSM) and RNG $\varepsilon$-$k$ model was found to produce noisy data that prevented construction of response surface models.

1. Introduction

Train aerodynamic optimization is always a multi-objective problem meaning that several objectives such as drag, crosswind stability or aeroacoustic noise must be optimized simultaneously. This requires that compromises are made between objective functions. Improving one objective leads often to deterioration of other and the whole process requires large number of costly experimental and numerical evaluations. Besides, these is no guarantee that an optimal design will be obtained. Another issue is that often several optimal designs are preferred producing a more flexible shape of the train that can easily be adapted to different needs. Thus a rigorous numerical algorithm that is capable of analyzing a design space in a systematic way and providing a design that fulfills specifications is desired. Such an optimization procedure has in past been prohibited due to large computational effort required for evaluation of large number of Navier-Stokes runs. The present paper suggest simplification of the procedure by using approximations of objective functions that will replace costly Navier-Stokes solutions. Such approximations are often denoted metamodels or surrogate based models and the basic idea behind these is to use relatively small number of numerical experiments (runs of Navier-Stokes solver) to construct an approximate model that is valid in the entire design space. If the true nature of a Navier-Stokes solution is $y = f(x)$ then a metamodel is $\hat{y} = g(x)$ where $x = (x_1, x_2, ..., x_N)$ are design variables. A metamodel contains an error that in physical experiments is partly due to the modeling error and partly due to measurement errors. In numerical experiments the modeling error is a result of the choice of a metamodel while the closest to measurement error (which is random in physical experiments) is numerical error. Ones such a metamodel is constructed, a direct relationship between design variables and objective is available. Furthermore, as the evaluation of the objective functions using metamodels is inexpensive, fast analysis of the design domain using e.g. evolutionary algorithm is possible. The paper is organized as follows. Chapter 2 describes the process of construction of metamodels used in the present work. This is followed by the description of the multi-objective
optimization procedure in Chapter 3. Finally, in chapter 4 the necessary development of the suggested methodology is discussed.

2. Construction of metamodels

Geometric parameterisation

The analysis of the aerodynamic properties of a train starts with geometric parameterization of the shape of a train. This is not a trivial task as the shape of a train is complex and described in terms of computer aided design (CAD) language. However, a CAD description of the geometry is complicated and not practical for the purpose of optimization using metamodels. A description of a realistic train geometry using such variables leads to a too large number of variables for practical optimization purposes as the computational cost of an optimization problem is directly influenced by the number of design variables. There is ongoing research in the field of the geometric parameterization with the aim to decrease the number of design variables where the idea is to control several geometric variables by a single design variable and in such a way decrease the total number of design variables. While waiting for this new geometric parameterization technology to be available, limited number of traditional design variables will be used in the present paper. Beside the choice of the geometric design variables, a choice of design space constraints is important for an accurate representation of the aerodynamic properties by a metamodel. By choosing a proper design space constrains, the design domain can be narrowed and thus the accuracy between the design points can be increased. Furthermore, it is common procedure to scale the design variables into the range between $-1$ and $1$ in order to simplify calculations [11]. These new scaled variables are called coded variables.

In the present work, two different optimization cases are studied. The aim of the first case is to optimize the shape of the front of a generic train for the crosswind stability. The shape of the train is the one studied in experiments by Chiu and Squire [1] and numerical studies by Hemida and Krajnović [4,5].

The profile of the cross section of this model is defined by the following equation

$$|y|^n + |z|^n = c^n$$ (1)

The coefficient of curvature, $n$, varies linearly along the front of the train according to the equation:

$$n = \frac{2 - q}{b} z + q$$ (2)

where $q$ is the value of $n$ far from the front at the body of the train and $b$ is the length of the front. The second equation that describes the shape of the front from a lateral side is

$$\frac{z^2}{b^2} + \frac{y^2}{c^2} = 1$$ (3)

Here, $c = \frac{h}{2}$ and $h = 3.0$ [m] is the height of the train (Figure 1a). The length of the train excluding the front and the rear (which are identical) is 30 [m].
Figure 1. Shape of the front of the train from a side and from in front of the train. b) Position of the vortex generators on the rear of the ICE2 train used in the present work. View is from the rear of the train.

The design constraints are $0.64h \leq b \leq 1.28h$ and $4 \leq n \leq 6$. Such constrains were chosen in order to represent realistic length of the front and roundedness of the cross section of the train. The choice of the length of the train front was in particular chosen to represent different rail vehicles from a commuter train to a high-speed train. Flow situations with $30^\circ$ yaw angle of the cross wind is studied in this paper. At the inlet of the computational domain a constant velocity of $64.7 \text{m/s}$ was applied. Moving floor boundary condition was applied at the ground and no slip boundary conditions were prescribed at the tunnel wall (which was in a form of a half a cylinder). Wall functions are used on the surface of the train. The outlet boundary condition for the velocities was homogeneous Neumann.

The second shape that is optimized in the present work is that of vortex generators placed on the rear of an ICE 2 high-speed train with purpose of decrease of pressure drag (Figure 1b). Vortex generators (from now denoted VGs) act as small wings producing the longitudinal tip vortices shown in our simulations in Figure 2b. The function of these longitudinal vortices is to sweep the high energy air from the inviscid portion of the flow-field or higher portion of the boundary layer to the inner parts of the boundary layer. As the energy is added from the high-energy air to retarded air inside the boundary layer, the separation is delayed leading to an increased base pressure and lower drag of the train.

In the present study a relatively short train is used containing only 1.25 lengths of a car of a real ICE2 train (Figure 1b). Due to such a short train, the aerodynamic drag is dominated by the pressure drag and we expect the vortex generating devices to decrease the total drag. However, in a real situation of a two hundred meter (or longer) train, drag is dominated by the shear forces and the effect of the vortex generators on the drag reduction would be rather limited. Besides, as we will see later, the height of the optimal vortex generator is similar to the boundary layer thickness at the location of the placement of VGs making them impractical for long trains. Vortex generators are placed just before the slanted surface of the rear of the train, at the position of the separation on the train without VGs.

The inlet and the floor boundary condition was $56 \text{m/s}$, the roof and the lateral walls were treated as slip surfaces while the outlet was homogeneous Neumann boundary condition for the velocities. Wall functions were used as a boundary condition on the surface of the train.

Figure 2 An example of VGs used in the present study with two design variables, $\alpha$ and $H$. b) Longitudinal tip vortices produced as a result of VGs (here visualized using streamlines).
The shape of the VG is shown in Figure 2a and two design variables: the height, $H$, of the VG and the angle, $\alpha$, of the streamwise slanted side of VGs were varied in the present study. Design constraints were at first set as $6\text{cm} \leq H \leq 30\text{cm}$ and $24^0 \leq \alpha \leq 46^0$. However, later three additional designs were added with the height $H = 38\text{cm}$, to original six designs.

**Experimental design**

A design of experiments is a sequence of experiments within design space that will be performed. This is a critical step as the quality of the metamodel is dependent on the choice of points in design variable space from which the model will be constructed. Experimental design techniques, so called design of experiments (DOE) were originally developed for physical experiments but are often used for design of computer experiments.

![Figure 3 Center composite design for optimization of the front of the generic train.](image)

Center composite design (CCD) was used as DOE in the present study. The two DOEs are presented in Figures 3 and 4, for the optimization of the front of the train and the VGs, respectively. Nine designs were first used for the optimization of the front of the train and VGs. However, the number of designs for VGs was later increased to twelve of which eleven were used for construction of the model. The design with $\alpha = 24^0$ and $H = 38\text{cm}$ was not used in the present study.

![Figure 4 Center composite designs for optimization of the VGs.](image)
Computer experiments at the design points

Prediction of aerodynamic forces and moments is very much dependent on the numerical method used for the simulation. Despite all known problems with accuracy of Reynolds-Averaged Navier-Stokes (RANS) methods, they were used here for their simplicity and relatively small computational effort. However, the question of appropriate RANS model remains. One aim of the present paper was to investigate if the optimization procedure is dependent on the turbulence model used. Four different turbulence models were used in the present paper: the standard \( k-\varepsilon \) model, the realizable \( k-\varepsilon \) model [13], the RNG \( k-\varepsilon \) model and the Reynolds Stress Model (RSM) model. The objective functions in the present work are drag, lift and side force coefficients, for the front of the train and drag and lift coefficients for the case with VGs.

All calculations in the present work are made using commercial finite volume solver Fluent 6.3.26. Incompressible flow was assumed in simulations and SIMPLE algorithm was used for pressure-velocity coupling. Second-order upwind scheme was used for discretization of momentum, \( k \) and \( \varepsilon \) – equations.

Polynomial response surface approximation

Once the computer experiments (CFD simulations) have provided the values of the objective functions in the design points, the construction of metamodel can begin. There are several choices for metamodels such as polynomial response surfaces (RS), radial basis neural networks and Kriging approximations and in the present paper only the RS will be used. The approximation of the true response in a RS is represented by low order polynomials which in the present paper are quadratic and cubic. For example, a cubic RS model is:

\[
\hat{y} = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} x_i x_j + \sum_{i=1}^{n} \beta_{ii} x_i^2 + \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} x_i x_j + \sum_{i=1}^{n} \beta_{ii} x_i^3
\]

where \( n \) is number of design variables and \( \beta_1, \beta_{ij}, \beta_{ii}, \beta_{ij}, \beta_{ii} \) are regression coefficients. The regression coefficients are determined by a least square regression. The RS can be expressed in matrix notation as \( \hat{y} = X^T b \) where \( b = (X^T X)^{-1} X^T y \) and \( X \) is the matrix containing the experimental design.

In order to measure the goodness of the fit both the coefficient of multiple determination \( R^2 \) and \( R^2 \) –square adjusted ( \( R^2_a \) ) were used.

The coefficient of multiple determination \( R^2 \) measures the fraction of variation in data captured by response surface.

\[
R^2 = \frac{SS_R}{SS_T} = 1 - \frac{SS_E}{SS_T}
\]

where \( SS_E \) is the sum of squared approximation errors at the \( n_p \) sampling points, \( SS_T \) is the true response’s sum of squared variations from the mean \( \bar{y} \), and \( SS_R \) is the approximation’s sum of squared variations from the mean, i.e.

\[
SS_E = \sum_{i=1}^{n_p} (y_i - \hat{y}_i)^2, \quad SS_T = \sum_{i=1}^{n_p} (y_i - \bar{y})^2, \quad SS_R = SS_T - SS_E = \sum_{i=1}^{n_p} (\hat{y}_i - \bar{y})^2
\]
A better suited measure for assessing predictive accuracy is the $R$-square adjusted ($R^2_a$) defined as

$$R^2 = 1 - \frac{SS_E/(n_p - n_P)}{SS_T/(n_p - 1)}$$

(4)

where $n_p$ is the number of regression coefficients. Both $R^2$ and $R^2_a$ range between zero and one, and the higher value indicates better predicting accuracy of the response surface.

Although the full model was fit at first, it is possible that this is not an appropriate model, i.e. it is possible that a model based on a subset of regressors in the full model may be superior. In the present work, a backward elimination procedure based on the $t$ statistic is used to discard terms and improve the prediction accuracy. The $t$ statistics of the fitting coefficient is defined as its value divided by an estimate of the standard error of the coefficient.

In the backward elimination we begin with a model that includes all candidate regressors (i.e. the full model) and then the partial $t$ statistic is computed for each regressor as if it were last variables to enter the model. The smallest of these partial $t$-statistics is compared with preselected value, $t_{out}$ and if it is less than $t_{out}$, that regressor is removed from the model. Here we use a common rule of thumb which says that regressor terms with absolute value of $t$ larger than $t_{out} = 2$ are significant at a 95% confidence level.

**Variable selection for the front of the train case**

Here we shall only demonstrate how the model can be improved for the case of the optimization of the front of the train at a yaw angle of $30^\circ$ and only for the case when the realizable $k - c$ turbulence model was used. The case of optimization of VGs and using different turbulence models is done in similar ways.

According to Table 2, the full quadratic response surface model for the drag coefficient has $R^2_a$ of 0.9917. Determination of the mixed-term regressor $\beta_{12}$ involves a large standard error (exposed by a low absolute value of $t$ in Table 1). Discarding this term from the model improves the fit and increases $R^2_a$ to 0.9927. However, discarding the quadratic term $\beta_{22}$ in the next step of the backward elimination leads to lower $R^2_a$ of 0.9883. Thus elimination of this term does not improve the fit and the best quadratic RS of the drag coefficient is:

$$\hat{C}_D = 0.2787 + 0.0129x_1 - 0.0101x_2 - 0.002x_1^2 + 0.0017x_2^2$$

(5)

Similar procedure of backward elimination is made for the lift and the side force coefficients. The results of the procedure are presented in Tables 3-5 and the resulting RS models are

$$\hat{C}_L = 0.0217 - 0.0062x_1 + 0.0078x_2 + 0.0035x_1^2 - 0.0015x_2^2$$

(6)

$$\hat{C}_S = 0.2837 + 0.0135x_1 - 0.0095x_2 - 0.002x_1^2 + 0.001x_2^2$$

(7)
<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Full</th>
<th>Reduced</th>
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<td>$\beta_0$</td>
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<td>$\beta_1$</td>
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<td>$\beta_2$</td>
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<tr>
<td>$\beta_{12}$</td>
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<tr>
<td>$\beta_{21}$</td>
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<td>$\beta_{22}$</td>
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Table 1 Regressor values and their $t$ statistics from regression analysis for RS of $C_D$.

<table>
<thead>
<tr>
<th>Removed coefficients</th>
<th>$R^2$</th>
<th>$R_a^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{12}$</td>
<td>0.9964</td>
<td>0.9927</td>
</tr>
<tr>
<td>$\beta_{22}$</td>
<td>0.9927</td>
<td>0.9883</td>
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</table>

Table 2 Coefficients of multiple determination used in backward elimination procedure for RS of drag coefficient $C_D$.

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Full</th>
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<tbody>
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<td>$\beta_0$</td>
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<td>22.52</td>
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<tr>
<td>$\beta_1$</td>
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<td>$\beta_2$</td>
<td>13.96</td>
<td>14.86</td>
</tr>
<tr>
<td>$\beta_{12}$</td>
<td>-0.73</td>
<td>--------</td>
</tr>
<tr>
<td>$\beta_{21}$</td>
<td>3.60</td>
<td>3.83</td>
</tr>
<tr>
<td>$\beta_{22}$</td>
<td>-1.54</td>
<td>-1.64</td>
</tr>
</tbody>
</table>

Table 3 Regressor values and their $t$ statistics from regression analysis for RS of $C_L$.

<table>
<thead>
<tr>
<th>Removed coefficients</th>
<th>$R^2$</th>
<th>$R_a^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{12}$</td>
<td>0.9895</td>
<td>0.9786</td>
</tr>
<tr>
<td>$\beta_{22}$</td>
<td>0.9823</td>
<td>0.9717</td>
</tr>
</tbody>
</table>

Table 4 Coefficients of multiple determination used in backward elimination procedure for RS of lift force coefficient $C_L$. 
The original RS was a second-order polynomial that was constructed over the design domain $6\text{cm} \leq H \leq 30\text{cm}$ and $24^\circ \leq \alpha \leq 46^\circ$. Once the RS was constructed, it was found that the minimal value of $C_p$ was at the corner of the design domain, i.e. for $H = 30\text{cm}$ and $\alpha = 46^\circ$. In order to explore if the design can be improved outside the design domain, two additional designs with $H = 38\text{cm}$ were added to the original six designs (Figure 3). Also here the $t$ statistics were used to eliminate regressors with insignificant or damaging influence onto the responses $\hat{C}_D$ and $\hat{C}_L$. When the design domain was expanded a new second order RS model for $\hat{C}_D$ was constructed. However, such a model was found to produce poor fit with the CFD data resulting in $R^2_a = 0.55$ after backward elimination procedure. Thus, the third order polynomial was applied resulting in $R^2_a = 0.7631$. Next step was to check if the 11 CFD simulations included outliers. This was done by computing studentized residuals defined as $r_i = \frac{e_i}{\sqrt{\hat{\sigma}^2(1-h_{ii})}}$ where $e_i = C_p - \hat{C}_D$ is the residual from the fitted model, $\hat{\sigma}^2 = \frac{y^T y - b^T X^T y}{n-p}$ and $h_{ii}$ is $i$ diagonal element of $H = X(X^T X)^{-1} X^T$. Most of the studentized residuals should lie in the interval $-3 \leq r_i \leq 3$, and simulations with studentized residuals outside of this interval can be unusual in respect to their response and are considered outliers [11]. Figure 5a shows that the design number 7 is a potential outlier. When this design was removed the $R^2_a$ increased to 0.8672.
The final cubic RS model is:

\[
\hat{C}_D = 0.1113 - 0.0095x_1 - 0.0014x_1x_2 - 0.0059x_2^2 + 0.0056x_1x_2^2 + 0.0015x_1^2
\]

(8)

Figure 5  
a) Studentized residuals for the VG case: before removing an outlier (asterisk), after the 7th design was removed (circles).  
b) Contour plot of the cubic RS of \( C_D \) for VG case. The optimal design is denoted with \( X \).

Unfortunately it was found that neither quadratic or cubic RS polynomial functions were capable to fit the response of \( \hat{C}_L \). This can be due to well known problems of RANS models to predict lift force coefficients or to rapid change in lift.

**Validation of metamodels**

Beside the measure of fit described above, another test in form of verification of the accuracy of the model prediction can be performed on the constructed metamodel in order to ensure its accuracy. This is done by constructing a new design that was not used for construction of the model and performing new computer experiment. The objective functions provided from this new simulation are then compared with the model prediction. For example for the train at 30° yaw angle a new CFD simulation of the flow around an additional train with \( n = 4.545 \) and \( b = 3.363[m] \) was made. The resulting force coefficients \( C_D, C_L \) and \( C_S \) were 0.2693, 0.0296 and 0.2739, respectively. Comparison with RS approximations shows the relative error of 0.6%, 2.8% and 0.3% for the \( C_D, C_L \) and \( C_S \), respectively. Obviously there is good agreement between numerical simulations and RS’s approximations.

**Turbulence models and numerical noise**

Before we discuss the optimization procedure, let us comment on the influence of turbulence model on metamodel and thereby on the optimal design. Results of the numerical simulation using the RNG \( k - \varepsilon \) model were found to be unreliable for the construction of models in the case of crosswind flows. Similar was found for the RSM model in the case of VGs. The cause for difficulties in using data from these simulations is due to incomplete converge which produced numerical noise in the objective functions. Although RS approximations are known to perform very robustly in case of noisy objective functions, neither quadratic or cubic RS approximations could give some reasonable fit in these two simulations. The standard \( k - \varepsilon \) model was on the other hand found to produce poor results for the flow around vortex generators.
The simple test of the influence of the turbulence model on the optimization was made by minimization of the three aerodynamical forces in the case of optimization of the shape of the train using the standard and the realizable $k-\varepsilon$ models. It was found that the identical optimal designs were found for minimal drag and side forces while very different designs were produced for minimal lift force between the two models. The explanation is found in Tables 2, 4 and 6. The $R_a^2$ for the drag and the side force coefficient is higher than for the lift force coefficient indicating better fit of the model with the CFD data. Although the problem of prediction of the lift force with RANS models is well known in vehicle aerodynamics these results show that special care must be taken when choosing the turbulence model. Only results from realizable $k-\varepsilon$ model are considered in the present paper.

Optimization based on metamodels

In the present paper, the case of the front shape optimization was treated as a multi-objective optimization problem while simple minimization of the drag coefficient was performed in the optimization of vortex generators. The multi-objective optimization problem of the front shape of the train was solved using an evolutionary multi-objective optimization procedure (so called real-coded genetic algorithm NSGA-II) by Deb et al. [2]. The NSGA-II algorithm was implemented in MATLAB. Running this genetic algorithm together with computer experiments (CFD simulations) would be extremely computer demanding. However, since the metamodels for each objective are available in form of simple polynomial expressions, the evaluation of generic algorithm is fast and efficient. The objective of such an algorithm is to find solutions (in form of combinations of objectives) such that there is no other solution for which at least one objective has better value while values of remaining objectives are the same or better. Solution obtained using this optimization procedure are called Pareto-optimal. The parameters chosen for the NSGA-II simulations are presented in Table 7.

<table>
<thead>
<tr>
<th>Population size</th>
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<td>Generations</td>
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<tr>
<td>Crossover probability</td>
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</tr>
<tr>
<td>Distribution parameter (for crossover)</td>
<td>20</td>
</tr>
<tr>
<td>Mutation probability</td>
<td>0.25</td>
</tr>
<tr>
<td>Distribution parameter (for mutation)</td>
<td>20</td>
</tr>
</tbody>
</table>

Table 7 Parameters used for the NSGA-II simulations.

A population of hundred train designs were regenerated hundred times resulting in hundred Pareto-optimal solutions shown in Figure 5a. This Pareto optimal set contains large number of solutions and a classification is needed in order to study alternative designs. Here a hierarchical clustering algorithm (K-mean algorithm) in MATLAB was used to identify a representative set of three solutions in case of train front optimization. Values of design variables and objectives for these designs are shown in Table 8. Figure 5 shows that these three solutions are uniformly distributed in the Pareto optimal front.

Cluster 1 shows that small roundedness of the train indicated with $n = 5.89$ and relatively short front are required for low lift force coefficients. On the other hand, such a combination produces maximum lift and side force coefficients. The opposite extremes of the force coefficients are found in cluster 3 where maximal roundedness ($n = 4$) and longest front produces minimal drag and side force coefficients for a price of maximal lift force coefficient. Clusters 2 is a compromise design that produces better performance than cluster 1 for drag and side force coefficients. However, this design requires very rounded cross section ($n = 4$) which decreases useful space in the train. Besides, the front of the train is longer and the resulting lift force coefficient is almost three times larger than in cluster 1. Thus cluster 1 is suitable for a commuter train due to relatively short length of the front. On the other hand, large saving in energy consumption and better stability (expressed in low side force) can be achieved if
relatively long front and well rounded cross sections can be used such as in cluster 3. This is applicable for high-speed trains.

Figure 5b shows the Pareto optimal front of objective functions $C_D$ vs. $C_L$ which are in conflict. The Pareto optimal front is linear for $0.255 \leq C_D \leq 0.283$ and it can be seen that a relatively small increase in drag (7%) gives around (48%) decrease in the lift force coefficients. Similar behavior of the objective functions was found in the Pareto optimal front of $C_S$ vs. $C_L$ (not shown here).

For the case of the optimization of VGs, the optimization was performed simply by minimizing obtained cubic RS. The resulting optimal VG has a height of $H = 32.63 \, \text{cm}$ and an angle of attack of $\alpha = 44.4^\circ$. It is interesting to see that the optimal height of the VG is slightly higher than the boundary layer thickness (around 30 cm) at the position of VGs. The present study shows that the passive flow control using optimal VGs results in a drag decrease of about 5%. However, this value is not representative for real trains which are much longer than the train used in the present test case. Although there is definitely a pressure drag reduction even for a longer train, the pressure drag contribution is relatively small for long trains and the total gain is relatively small. Besides, the height of optimal VGs seems to be correlated with the boundary layer thickness, meaning that application of VGs on long trains is not practical due to large size of control devices.

<table>
<thead>
<tr>
<th>Cluster</th>
<th>$n$</th>
<th>$b$</th>
<th>$C_D$</th>
<th>$C_S$</th>
<th>$C_L$</th>
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<td>1</td>
<td>5.89</td>
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<td>4</td>
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<td>3</td>
<td>4</td>
<td>3.94</td>
<td>0.255</td>
<td>0.260</td>
<td>0.038</td>
</tr>
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</table>

Table 8 Design variables and objective functions in three representative designs from Pareto optimal solutions.

4. Discussion and conclusions

Although the present paper has demonstrated an efficient shape optimization technique for aerodynamics of high-speed trains, it is obvious that there are several issues that require further investigations. A simple description of the geometry through geometry parameterization is
probably the major obstacle for putting the algorithm described here in production. The parameterization should not only be precise but also contain small number of design variables in order to decrease the computer effort for construction of metamodels. Another issue that has to be addressed is usage of an alternative to DOE, so called DACE which is better suited for design and analysis of computer experiments. Besides, use of other metamodels than response surfaces such as Kriging model and radial basis neural networks need to be explored. Quality of the data from numerical simulations used for the construction of any metamodel is of course crucial. As shown in the present paper, numerical noise due to poor convergence of a turbulence model can prevent any meaningful fit of the response surface approximation of data from the design of experiments. What is even worse is that two optimization procedures based on Navier-Stokes solutions using difference turbulence models can result in very different optimal designs. Thus the choice of turbulence model is essential. Turbulence models should be chosen with greatest care concerning their capability to predict the desired flow, its convergence (which can result in numerical noise) and computational effort. This is unfortunately difficult to achieve as no turbulence model can predict entire flow around a train. In particular regions with strong separations are problematic and can normally only be predicted with sufficient accuracy using time-dependent techniques such as large-eddy simulations or detached eddy simulations. However the large computational effort required for these techniques prevents their usage in optimization. The remaining approach is to use different turbulence models for prediction of different objective functions. However this requires an experienced user (CFD engineer) that can make appropriate choice of turbulence models. Despite all open questions, the suggested optimization technique is promising and will certainly be used for optimization of high-speed trains in the future.

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References


